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Prioritizing Water-Efficient Strategies in Renewable Energy Technologies Using Koch Snowflake Fuzzy Decision Support System

Serkan Eti[1,*], Serhat Yüksel[2,3], Hasan Dinçer[2,3], Edanur Ergün[2], Harun Çetinkaya[2], Merve Acar[2]

[1] Faculty of Applied Sciences, Marmara University, Istanbul, Turkey
[2] School of Business, Istanbul Medipol University, Istanbul, Turkey
[3] Department of Economics and Management, Khazar University, Baku, Azerbaijan

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ABSTRACT

Renewable energy projects provide significant environmental and economic benefits. However, they may also involve negative impacts and potential challenges, including excessive water consumption associated with some renewable energy technologies. In this context, a key problem is the uncertainty regarding which strategies should be prioritized to effectively reduce water consumption. This gap in the literature negatively affects both academic research and the development of national energy and environmental strategies. Therefore, the main purpose of this study is to prioritize strategies for reducing excessive water consumption in renewable energy technologies according to their importance levels. For this purpose, Koch Snowflake fuzzy sets are developed and integrated into the decision-making model to manage uncertainty more effectively. Moreover, cluster-based expert selection and the SIWEC and MABAC methods are employed together to obtain comprehensive and precise results. This study contributes to the literature by providing a systematic prioritization approach for evaluating strategies aimed at reducing excessive water consumption in renewable energy technologies under uncertainty. The findings indicate that the most effective investment strategy for reducing water consumption is the development of battery technologies that use water efficiently.

1. Introduction

Renewable energy projects provide many environmental and economic benefits. However, they also have some negative aspects and potential problems. It is very important to know and take these negative aspects into consideration to develop more sustainable and balanced energy strategies. Renewable energy technologies can lead to high water consumption in some applications. In concentrated solar energy projects, wet cooling technology is used for electricity generation [1]. This situation can cause excessive water consumption. This situation can also occur in some biomass energy projects. Corn and some other plants are needed to produce biofuels such as ethanol. These plants are grown in large agricultural areas that require irrigation. In addition, high amounts of water evaporation can occur during geothermal energy production. Water losses can also occur if the hot water and steam from geothermal sources are not re-injected underground. Hydroelectric energy projects can also experience large water losses due to evaporation. Similarly, evaporation losses

* *Corresponding author.*
E-mail address: seti@marmara.edu.tr

increase even more during dry periods [2]. This situation leads to the loss of potential resources that can be used in agriculture and drinking water. Excessive water consumption in renewable energy projects is a significant problem, especially for certain technologies and geographical regions. This situation makes it difficult for local people, agriculture and ecosystems to access water.

In renewable energy projects, technological, administrative and policy-based measures can be taken to prevent excessive water consumption. By considering dry cooling systems, less water can be consumed in the electricity generation process of solar energy projects. Similarly, waterless panel cleaning systems contribute to achieving this goal. Robotic waterless cleaning systems can be used to reduce excessive water consumption in wind turbines. Low evaporation dam design also reduces water waste in hydroelectric energy projects. Furthermore, closed-circuit cooling systems can be used in geothermal energy. This can prevent excessive evaporation [3]. Efficient irrigation systems can be applied in agricultural areas to reduce water loss in bioenergy production. On the other hand, the development of battery technologies that use water efficiently also contributes to achieving this goal. To implement these applications, businesses need to have certain competencies. Increasing research studies, making effective legal regulations, developing qualified personnel and easy access to financial resources are quite necessary in this process [4]. Resources such as qualified personnel, financing and research budget are generally limited. Therefore, determining the most important factors is necessary to ensure optimum resource utilization. The fact that there are few studies in literature that systematically determine the most important factors is a significant academic and practical deficiency. This research gap in literature creates a problem for preparing national energy or environmental strategies. When it is not known which factors are critical, the decisions taken may be incomplete or ineffective.

To satisfy this research gap in literature, the aim of this study is to determine priority strategies to reduce excess water use in renewable energy technologies. To achieve this objective, a new model is generated by combining different methods, such as clustering based expert selection, SIWEC and MABAC. On the other side, Koch Snowflake fuzzy sets are also created in this study to handle uncertainties. Numerous strategies have been proposed in the literature to reduce water consumption in renewable energy technologies. Nevertheless, there is no generally accepted consensus on the importance levels of these strategies. This situation makes it difficult to effectively conduct both academic research and practical policy development processes. One of the main motivations of this study is to contribute to this uncertainty by prioritizing among these strategies using scientific methods. In summary, this study aims to find the answers for the following research questions. (1) What are the prominent strategies in literature to reduce excessive water consumption? (2) What are the most important decision criteria affecting the applicability of these strategies? (3) How can a decision-making model be developed that can evaluate the importance levels of these strategies under uncertainty?

This study contributes to the systematic prioritization approach missing in the literature by analyzing the importance levels of strategies to reduce excessive water consumption in renewable energy technologies under uncertainty. The proposed model has some critical superiorities by comparing with the previously generated ones. The details of these issues are indicated as follows. (1) The use of Koch Snowflake fuzzy sets in decision-making models provides significant advantages both theoretically and practically. The Koch Snowflake structure is based on fractal geometry. With the help of this situation, uncertainties in complex and multi-layered systems can be represented more successfully. It provides results that contain finer details than classical and some advanced fuzzy sets. Fractal-based structures can produce more sensitive responses to small changes. This increases the sensitivity of decision-making processes. (2) Integrating the clustering-based expert selection technique into the decision-making model provides both methodological advantages and significant contributions to literature. In real life, experts have many demographic and professional differences such as years of experience, field of expertise, academic background, and sectoral experience. Therefore, giving equal weight to each expert increases the risk of bias and error in the evaluation process. The clustering-based approach analyzes these differences statistically. Owing to this situation, groups experts with similar characteristics and determines the weights objectively. Weighted expert opinions increase the sensitivity and accuracy of the model. This allows more reliable and valid results to be achieved.

Developing a value-based, alternative approach to reducing water consumption in renewable energy technologies is critical for environmental sustainability and a human-centered development approach. In this context, R&D and digitalization activities ensure technical efficiency and serve value-based goals such as conserving resources, preventing waste and reducing environmental impact. Viewing water as a strategic natural resource requires the restructuring of production processes in accordance with our stewardship responsibilities on Earth [5]. Digital technologies prevent waste in energy production systems by enabling real-time monitoring, modelling and optimization of water use [6]. Research and development activities facilitate the creation of equipment that uses less water and its integration into energy infrastructure with innovative, water-sensitive solutions [7]. These technological and scientific initiatives support an ethical approach to production and consumption, prioritizing public interest, justice and resource conservation [8]. Zahedi *et al.,* [9] have demonstrated that hybrid renewable systems implemented in thermal power plants contribute to the conservation of natural resources by significantly reducing water consumption and carbon emissions through R&D-based cycle designs. Adomako and Tran [10] emphasized that strengthening R&D in sustainable energy investments significantly improves environmental and ethical performance criteria.

The success of strategies aimed at reducing water consumption in renewable energy technologies largely depends on choosing the right location and considering geographical suitability criteria. The efficiency of these technologies and their impact on water consumption are directly shaped by the characteristics of the physical environment, climatic conditions, and groundwater resources. Inappropriate energy investments in water-sensitive areas can increase the environmental burden. Furthermore, such investments can result in the waste of social resources and fail to produce long-term benefits. This situation highlights the need for an approach that prioritizes the fair and balanced use of resources. Decisions made in site selection processes that consider ethical responsibility, social welfare and justice principles alongside technical aspects will strengthen environmental and social sustainability [11]. Richards *et al.,* [12] found that large-scale solar energy investments in areas identified as suitable using multi-criteria decision-making methods could reduce CO_2 emissions by over 51,000 tones per year and save millions of dollars. Zhao *et al.,* [13] emphasized that, in the site selection model developed for wind-solar storage power plants, evaluating geographical suitability alongside technical and social criteria reduces environmental risks and adds a multidimensional approach to decision-making. Dawoud *et al.,* [14] found that the right site selection for solar-powered desalination investments in arid regions can reduce pressure on groundwater resources by up to 30%.

The feasibility of projects aimed at reducing water consumption in renewable energy technologies largely depends on the effectiveness of innovative financing models. Financing mechanisms that priorities risk sharing is needed to encourage the adoption of low-water consumption technologies developed in regions sensitive to water scarcity [15]. Such mechanisms should be structured to produce fair and long-term benefits. Such models ensure financial sustainability and enable the transfer of resources to projects that prioritize public value creation [16]. Unlike traditional credit models, financial instruments that are structured based on environmental and social impact are becoming increasingly important. These instruments contribute to the protection of natural resources and the promotion of social welfare. The models developed in this context reflect an economic understanding based on ethical responsibility in financial applications [17]. Myronchuk *et al.,* [18] analyzed the profitability and risk profiles of sustainable development projects using Monte Carlo simulation to assess financial feasibility. The study revealed that tools such as green bonds, government guarantees, and diversification can reduce uncertainty in these projects and strengthen financial sustainability. Naz *et al.,* [19] state that, when evaluated within the scope of innovative financing models, Sukuk increases investor confidence through strong corporate governance mechanisms. This structure ensures that renewable energy projects contribute to environmental and social sustainability goals on an ethical basis.

According to Hassan *et al.,* [20], the transformation process aimed at reducing water consumption in renewable energy technologies can only be made sustainable through effective policy incentives and widespread capacity development efforts. A guiding and regulatory legal framework ensure a secure investment environment. At the same time, raising social awareness through education directly affects the rate at which technologies are adopted [21]. Policy incentives facilitate the implementation of water-efficient technologies and prevent resource waste [22]. Education and capacity-building activities support the production of technical knowledge, as well as the development of responsible and public-interest-oriented behaviors [23]. Together, these two criteria form the basis for comprehensive transformation in terms of regulatory and ethical responsibility. Saleh and Hassan [24] determined the importance of policy incentives in reducing the environmental impact of renewable energy technologies and education-based capacity development efforts. They underlined that these efforts support an ethical transformation that prioritizes the public good and the efficient use of resources. Samoraj *et al.,* [25] identified that closed-loop systems in algal biorefineries have the potential to reduce environmental impacts, and that these technologies can be scaled up to an industrial level with appropriate policy incentives.

The results of the literature review revealed that a variety of criteria are important for reducing water consumption in renewable energy technologies. Value-based alternative approaches are crucial for environmental sustainability and ethical responsibility, considering public interest. In this context, R&D and digitalization activities can increase the efficiency with which resources are used in production processes and prevent waste. Site selection and geographical suitability are vital for reducing the environmental risk of investments, particularly in water-sensitive regions. In addition to technical adequacy, these factors should also consider principles of justice and fairness. Innovative financing models increase project feasibility and prioritize social benefits through ethical financial structures. Finally, effective policy incentives and capacity-building programs enable the widespread adoption of technologies and behavioral change based on awareness. Taken together, these criteria highlight the necessity of a holistic, value-based approach to ensure a long-term, fair and sustainable energy transition.

2. Methodology

This manuscript, which is created to reduce water use in renewable energy technologies, includes a hybrid fuzzy decision-making methodology. The methodology included in the manuscript consists of three stages. In the first stage, the selection of appropriate decision makers (DMs) is carried out objectively. After the selection of appropriate DMs with cluster analysis, the criteria determining the use of water in renewable energy technologies are prioritized with the SIWEC method. In the last stage, the strategies for reducing water use in renewable energy technologies are ranked using the MABAC method. The three-stage methodology included in the manuscript is visually presented in Figure 1.

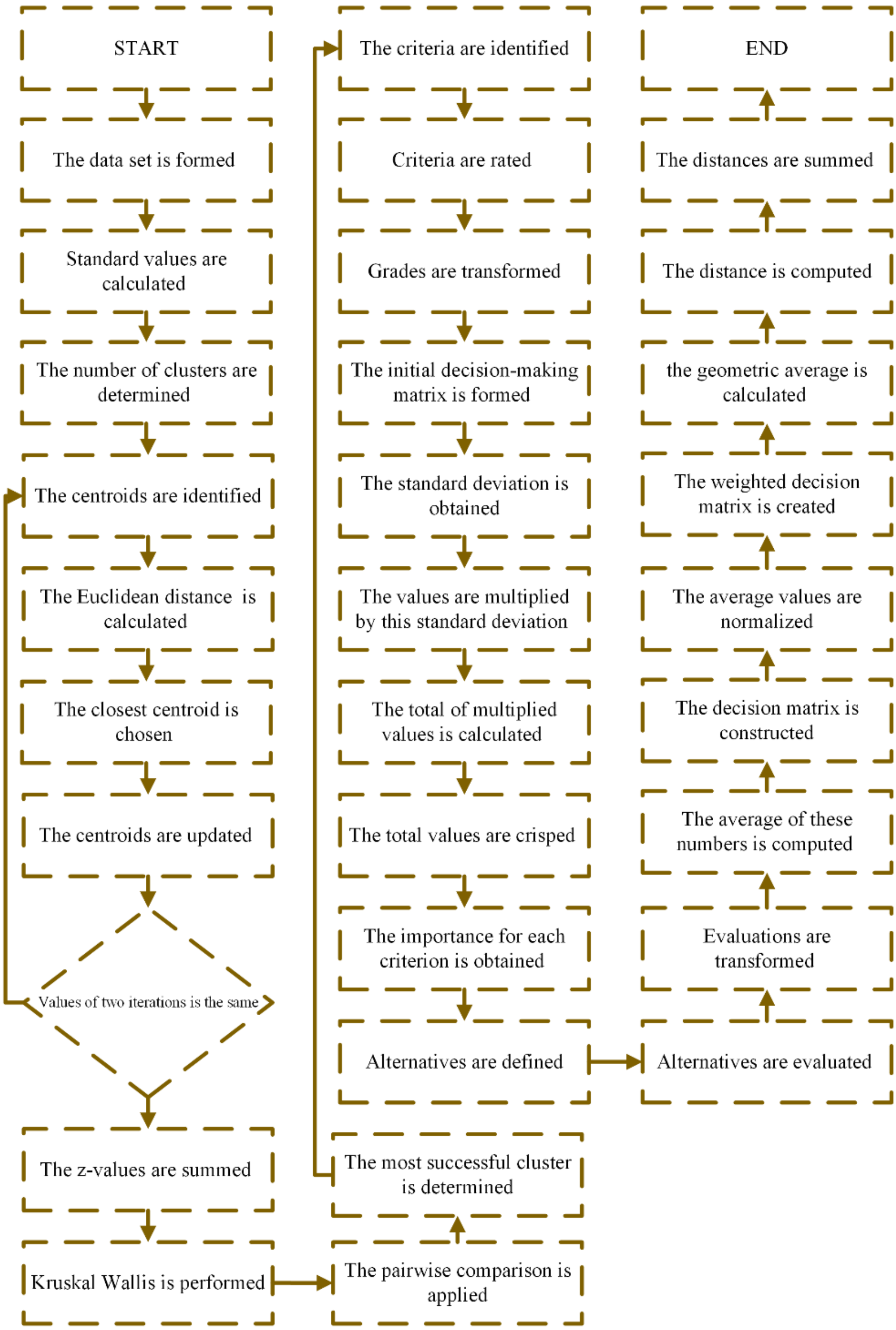

Fig. 1. The Three-Stage Methodology

Since DMs respond with linguistic expressions during the evaluation process, uncertainty must be minimized in the analysis process and calculation. For this purpose, fuzzy sets are used. This manuscript proposes Koch snowflake fuzzy sets. The main reason for this is that the Koch snowflake shape has a fractal structure and shows a similar geometric shape at every scale. With this feature, this set is used in the analysis in the manuscript as it best expresses the scaling of linguistic expressions.

2.1. Koch Snowflake Fuzzy Sets

A Koch snowflake fuzzy set $\left(\tilde{\tilde{\mathfrak{F}}}\right)$ is identified with Equation (1) [26].

$$\tilde{\tilde{\mathfrak{F}}} = \left\{\left\langle \mathfrak{u}, \left(\mu_{\tilde{\tilde{\mathfrak{F}}}}(\mathfrak{u}), \vartheta_{\tilde{\tilde{\mathfrak{F}}}}(\mathfrak{u})\right) | \mathfrak{u} \in \mathfrak{U}\right\}\right. \tag{1}$$

Wherein $\mathfrak{U}$ is a universe of discourse. In addition, $\mu: \mathfrak{U} \rightarrow [0,1]$ and $\vartheta: \mathfrak{U} \rightarrow [0,1]$ are named membership and non-membership functions of $\mathfrak{u}$ to $\tilde{\tilde{\mathfrak{F}}}$. Also, the elements of this set satisfy the condition in Equation (2).

$$0 \leq \mu_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) + \vartheta_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) \leq 1 \tag{2}$$

Wherein κ is the dimension of Koch snowflake fractal and equal to $\frac{\log(4)}{\log(3)}$. Moreover, the indeterminacy function is defined as Equation (3)

$$\pi_{\tilde{\tilde{\mathfrak{F}}}}(\mathfrak{u}) = \sqrt[\kappa]{1 - \mu_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) - \vartheta_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u})} \tag{3}$$

Assume $\tilde{\mathcal{X}}$ and $\tilde{\mathcal{Y}}$ be two Koch snowflake fuzzy number. So, some operators such as aggregate, multiplication etc. are determined by Equations (4) - (8).

$$\tilde{\mathcal{X}} + \tilde{\mathcal{Y}} = \left(\sqrt[\kappa]{\frac{\mu_{\tilde{\mathcal{X}}}^{\kappa} + \mu_{\tilde{\mathcal{Y}}}^{\kappa} - \mu_{\tilde{\mathcal{X}}}^{\kappa}\mu_{\tilde{\mathcal{Y}}}^{\kappa} - (1-\mathfrak{t})\mu_{\tilde{\mathcal{X}}}^{\kappa}\mu_{\tilde{\mathcal{Y}}}^{\kappa}}{1-(1-\mathfrak{t})\mu_{\tilde{\mathcal{A}}}^{\kappa}\mu_{\tilde{\mathcal{Y}}}^{\kappa}}}\, i\, \frac{\vartheta_{\tilde{\mathcal{X}}}\vartheta_{\tilde{\mathcal{Y}}}}{\sqrt[\kappa]{\mathfrak{t}+(1-\mathfrak{t})\left(\vartheta_{\tilde{\mathcal{X}}}^{\kappa} + \vartheta_{\tilde{\mathcal{Y}}}^{\kappa} - \vartheta_{\tilde{\mathcal{X}}}^{\kappa}\vartheta_{\tilde{\mathcal{Y}}}^{\kappa}\right)}}\right) \tag{4}$$

$$\tilde{\mathcal{X}} \times \tilde{\mathcal{Y}} = \left(\frac{\mu_{\tilde{\mathcal{X}}}\mu_{\tilde{\mathcal{Y}}}}{\sqrt[\kappa]{\mathfrak{t}+(1-\mathfrak{t})\left(\mu_{\tilde{\mathcal{X}}}^{\kappa} + \mu_{\tilde{\mathcal{Y}}}^{\kappa} - \mu_{\tilde{\mathcal{X}}}^{\kappa}\mu_{\tilde{\mathcal{Y}}}^{\kappa}\right)}}, \sqrt[\kappa]{\frac{\vartheta_{\tilde{\mathcal{X}}}^{\kappa} + \vartheta_{\tilde{\mathcal{Y}}}^{\kappa} - \vartheta_{\tilde{\mathcal{X}}}^{\kappa}v_{\tilde{\mathcal{Y}}}^{\kappa} - (1-\mathfrak{t})\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\vartheta_{\tilde{\mathcal{Y}}}^{\kappa}}{1-(1-\mathfrak{t})\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\vartheta_{\tilde{\mathcal{Y}}}^{\kappa}}}\right) \tag{5}$$

$$\lambda\tilde{\mathcal{X}} = \left(\sqrt[\kappa]{\frac{\left[1+(\mathfrak{t}-1)\mu_{\tilde{\mathcal{X}}}^{\kappa}\right]^{\lambda} - \left(1-\mu_{\tilde{\mathcal{X}}}^{\kappa}\right)^{\lambda}}{\left[1+(\mathfrak{t}-1)\mu_{\tilde{\mathcal{X}}}^{\kappa}\right]^{\lambda} - (\mathfrak{t}-1)\left(1-\mu_{\tilde{\mathcal{X}}}^{\kappa}\right)^{\lambda}}}, \frac{\sqrt[\kappa]{\mathfrak{t}}\vartheta_{\tilde{\mathcal{X}}}^{\lambda}}{\sqrt[\kappa]{\left[1+(\mathfrak{t}-1)\left(1-\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\right)\right]^{\lambda} + (\mathfrak{t}-1)\vartheta_{\tilde{\mathcal{X}}}^{\lambda\kappa}}}\right) \tag{6}$$

$$\tilde{\mathcal{X}}^{\lambda} = \left(\frac{\sqrt[\kappa]{\mathfrak{t}}\mu_{\tilde{\mathcal{X}}}^{\lambda}}{\sqrt[\kappa]{\left[1+(\mathfrak{t}-1)\left(1-\mu_{\tilde{\mathcal{X}}}^{\kappa}\right)\right]^{\lambda} + (\mathfrak{t}-1)\mu_{\tilde{\mathcal{X}}}^{\lambda\kappa}}}, \sqrt[\kappa]{\frac{\left[1+(\mathfrak{t}-1)\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\right]^{\lambda} - \left(1-\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\right)^{\lambda}}{\left[1+(\mathfrak{t}-1)\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\right]^{\lambda} - (\mathfrak{t}-1)\left(1-\vartheta_{\tilde{\mathcal{X}}}^{\kappa}\right)^{\lambda}}}\right) \tag{7}$$

$$\tilde{\mathcal{X}}^{C} = (\vartheta_{\tilde{\mathcal{X}}}, \mu_{\tilde{\mathcal{X}}}) \tag{8}$$

Wherein $\mathfrak{t}$ is positive value and generally considered 1. λ is nonnegative scaler. In addition, let $\tilde{\tilde{\mathfrak{F}}} = \left(\mu_{\tilde{\tilde{\mathfrak{F}}}}, \vartheta_{\tilde{\tilde{\mathfrak{F}}}}\right)$ be a Koch snowflake fuzzy number. Then, the score function of $\tilde{\tilde{\mathfrak{F}}}$ is computed using Equation (9).

$$SF\left(\tilde{\tilde{\mathfrak{F}}}\right) = \mu_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) - \vartheta_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) \tag{9}$$

At the same time, the accuracy function of $\tilde{\tilde{\mathfrak{F}}}$ is calculated with the help of Equation (10).

$$AF\left(\tilde{\tilde{\mathfrak{F}}}\right) = \mu_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) + \vartheta_{\tilde{\tilde{\mathfrak{F}}}}^{\kappa}(\mathfrak{u}) \tag{10}$$

Let $\tilde{\tilde{\mathfrak{F}}}_i$ be a sequence of Koch snowflake fuzzy numbers. Then, the Koch snowflake fuzzy weighted averaging operator is identified with Equation (11).

$$KSFWA(\widetilde{\mathfrak{F}}_i)=\left(\begin{array}{c}\sqrt[\kappa]{\dfrac{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\mu_i^{\kappa}\right)^{w_i}-\prod_{i=1}^{k}\left(1-\mu_i^{\kappa}\right)^{w_i}}{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\mu_i^{\kappa}\right)^{w_i}-(\mathfrak{f}-1)\prod_{i=1}^{k}\left(1-\mu_i^{\kappa}\right)^{w_i}}},\\ \dfrac{\sqrt[\kappa]{\mathfrak{f}}\prod_{i=1}^{k}(\vartheta_i)^{w_i}}{\sqrt[\kappa]{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\left(1-\vartheta_i^{\kappa}\right)\right)^{w_i}+(\mathfrak{f}-1)\prod_{i=1}^{k}(\vartheta_i)^{\kappa w_i}}}\end{array}\right) \tag{11}$$

Wherein w represents the weights of fuzzy numbers and $\sum_{i=1}^{k} w_i = 1$. k is the amount of Koch snowflake fuzzy numbers. In addition, the Koch snowflake fuzzy weighted geometric operator is shown by Equation (12).

$$KSFWG(\widetilde{\mathfrak{F}}_i)=\left(\begin{array}{c}\dfrac{\sqrt[\kappa]{\mathfrak{f}}\prod_{i=1}^{k}(\mu_i)^{w_i}}{\sqrt[\kappa]{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\left(1-\mu_i^{\kappa}\right)\right)^{w_i}+(\mathfrak{f}-1)\prod_{i=1}^{k}(\mu_i)^{\kappa w_i}}},\\ \sqrt[\kappa]{\dfrac{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\vartheta_i^{\kappa}\right)^{w_i}-\prod_{i=1}^{k}\left(1-\vartheta_i^{\kappa}\right)^{w_i}}{\prod_{i=1}^{k}\left(1+(\mathfrak{f}-1)\vartheta_i^{\kappa}\right)^{w_i}-(\mathfrak{f}-1)\prod_{i=1}^{k}\left(1-\vartheta_i^{\kappa}\right)^{w_i}}}\end{array}\right) \tag{12}$$

The Euclidean distance between any two Koch snowflake numbers is obtained with Equation (13).

$$\mathcal{D}(\tilde{\mathcal{X}},\tilde{\mathcal{Y}})=\sqrt{\left(\left(\mu_{\tilde{\mathcal{X}}}^{\kappa}-\mu_{\tilde{\mathcal{Y}}}^{\kappa}\right)^2+\left(\vartheta_{\tilde{\mathcal{X}}}^{\kappa}-\vartheta_{\tilde{\mathcal{Y}}}^{\kappa}\right)^2+\left(\pi_{\tilde{\mathcal{X}}}^{\kappa}-\pi_{\tilde{\mathcal{Y}}}^{\kappa}\right)^2\right)} \tag{13}$$

Similarly, Taxicab distance between any two Koch snowflake numbers is estimated using Equation (14).

$$\mathcal{T}(\tilde{\mathcal{X}},\tilde{\mathcal{Y}})=\left|\mu_{\tilde{\mathcal{X}}}^{\kappa}-\mu_{\tilde{\mathcal{Y}}}^{\kappa}\right|+\left|\vartheta_{\tilde{\mathcal{X}}}^{\kappa}-\vartheta_{\tilde{\mathcal{Y}}}^{\kappa}\right|+\left|\pi_{\tilde{\mathcal{X}}}^{\kappa}-\pi_{\tilde{\mathcal{Y}}}^{\kappa}\right| \tag{14}$$

2.2. Clustering based DMs Selection

There are DMs in the sector who undertake similar job descriptions. However, the experience, age and knowledge of these DMs are different. Therefore, the most suitable DMs need to be determined. With cluster analysis, it is possible to classify DMs who undertake similar job descriptions. If the DM teams formed by classification are seen to differ statistically, the most successful DM team members according to the Z-score are selected as the most suitable DMs. The calculation step of this process is given below [27].

At the beginning of DMs selection, the data set is formed as Equation (15) for cluster analysis. The data set includes the professional information of DMs.

$$\mathcal{S}=\begin{bmatrix}\mathcal{s}_{11} & \cdots & \mathcal{s}_{1\mathfrak{p}}\\ \vdots & \ddots & \vdots\\ \mathcal{s}_{\mathfrak{d}1} & \cdots & \mathcal{s}_{\mathfrak{d}\mathfrak{p}}\end{bmatrix} \tag{15}$$

Wherein the values of $\mathfrak{d}$ and $\mathfrak{p}$ are the numbers of DMs and professional information of DMs, respectively. Due to the differences in professional information of DMs, standard values of the elements of the data set are calculated by Equation (16).

$$\mathcal{z}_{ij}=\frac{\mathcal{s}_{ij}-\bar{\mathcal{s}}_j}{\sigma_j} \tag{16}$$

Wherein $\bar{\mathcal{s}}$ and σ are the arithmetic average and standard deviation, respectively and computed with Equations (17) and (18).

$$\bar{\mathcal{s}}_j=\frac{\sum_{i=1}^{\mathfrak{d}}\mathcal{s}_{ij}}{\mathfrak{d}} \tag{17}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{\mathfrak{d}} \left(s_{ij} - \bar{s}_j\right)^2}{\mathfrak{d}}} \tag{18}$$

Afterwards, the number of clusters are determined according to Equation (19).

$$\mathcal{k} \cong \sqrt{\mathfrak{d}/2} \tag{19}$$

The number of clusters is the closest integer. Next, the centroids are identified. The initial centroids are selected from the data set randomly. Later, the Euclidean distance of each DM to each centroid is calculated using Equation (20).

$$\mathcal{D}_i^t\left(z_{ij}, centroid_j^t\right) = \sqrt{\sum_{j=1}^{\mathrm{p}} \left(z_{ij} - centroid_j^t\right)^2} \tag{20}$$

Wherein $\mathcal{D}_i^t$ refers to the Euclidean distance of i^{th} DM to t^{th} centroid. After that, each DM is assigned to the cluster of the closest centroid. The closest centroid is chosen according to Equation (21).

$$f_i = \left\{centroid \middle| \min_t \left(\mathcal{D}_i^t\left(z_{ij}, centroid_j^t\right)\right)\right\} \tag{21}$$

Afterwards, the centroids are updated regarding to the values of DMs in clusters with the help of Equation (22).

$$centroid_j^t = \frac{z_{rj}}{|cluster^t|} \tag{22}$$

Wherein $|cluster^t|$ means the number of DMs in t^{th} cluster and r refers to index of DMs in t^{th} cluster. If the f_i values in two consecutive iterations remain the same, the calculation is stopped. Until then, Equations (20) - (22) are calculated repeatedly. After the final clusters are constructed, the z-values of the DMs in each cluster are summed to identify the successful cluster by Equation (23).

$$tz_r^t = \sum_{j=1}^{\mathrm{p}} z_{rj} \tag{23}$$

Finally, the difference between the clusters is tested statistically with Kruskal Wallis. After the statistical difference is determined, pairwise comparisons are applied. At the end of the pairwise comparison, if it is statistically significant, the cluster with the highest tz is determined as the most successful cluster. In other words, DMs in this cluster are selected as appropriate DMs and evaluations are collected from these DMs.

2.3. SIWEC with Koch Snowflake Fuzzy Sets

SIWEC is the method by which weights are obtained by rating the criteria. SIWEC bases its assessment on the importance of DMs' broader assessment. SIWEC with Koch snowflake fuzzy sets is detailed below [28].

At the beginning, the criteria are identified. Next, these criteria are rated by DMs. These grades are transformed into Koch snowflake fuzzy numbers. Using these numbers, the initial decision-making matrix is formed as Equation (24).

$$\tilde{\mathcal{A}} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{\mathfrak{f}1} & \cdots & \tilde{a}_{\mathfrak{f}n} \end{bmatrix} \tag{24}$$

Wherein the values of n and $\mathscr{f}$ are the numbers of criteria and DMs in the most successful cluster, respectively. Next, the standard deviation $(\mathfrak{s})$ for each DM is obtained using score values of $\tilde{a}$ and the $\tilde{a}$ is multiplied by this standard deviation with Equation (25).

$$\tilde{\mathfrak{v}}_{ij} = \mathfrak{s}_i \tilde{a}_{ij} \tag{25}$$

Wherein the multiplication operator is defined in Equation (6). Then, the total of multiplied values is calculated by Equation (26).

$$\tilde{\mathfrak{T}}_j = \sum_{i=1}^{\mathscr{f}} \tilde{\mathfrak{v}}_{ij} \tag{26}$$

Wherein the aggregate operator is determined in Equation (4). Next, the total values are crisped with Equation (27).

$$\mathcal{T}_j = 1 + SF(\tilde{\mathfrak{T}}_j) \tag{27}$$

Finally, the importance for each criterion is obtained using Equation (28).

$$\mathscr{p}_j = \frac{\mathcal{T}_j}{\sum_{j=1}^{n} \mathcal{T}_j} \tag{28}$$

2.4. MABAC with Koch Snowflake Fuzzy Sets

MABAC is a decision model that uses the geometric mean of the criteria to rank the alternatives. MABAC with Koch snowflake fuzzy sets is detailed below [29].

At the beginning, the alternatives are defined. Next, these alternatives are evaluated by DMs. These evaluations are transformed into Koch snowflake fuzzy numbers. The average of these numbers is computed using Equation (11). With the average values, the decision matrix is constructed as Equation (29).

$$\tilde{\mathcal{D}} = \begin{bmatrix} \tilde{d}_{11} & \cdots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{m1} & \cdots & \tilde{d}_{mn} \end{bmatrix} \tag{29}$$

Wherein the number of alternatives is symbolized by m. After that, the average values are normalized with Equations (30) and (31).

$$\tilde{\mathfrak{n}}_{ij} = \tilde{d}_{ij}\ for\ Benefit \tag{30}$$

$$\tilde{\mathfrak{n}}_{ij} = \tilde{d}_{ij}^{C}\ for\ Cost \tag{31}$$

Afterwards, the normalized values are multiplied by the importance of criteria using Equation (32).

$$\tilde{\mathfrak{w}}_{ij} = \mathscr{p}_j \tilde{\mathfrak{n}}_{ij} \tag{32}$$

Wherein the multiplication operator is defined in Equation (6). Next, the geometric average for each criterion is calculated by Equation (33).

$$\tilde{\mathscr{g}}_j = \underset{j}{KSFWG}\left(\tilde{\mathfrak{w}}_{ij}\right) \tag{33}$$

Next, the distance between alternatives and geometric averages is computed with the help of Equation (34).

$$\Delta_{ij} = \begin{cases} \mathcal{D}\left(\widetilde{\mathfrak{w}}_{ij}, \widetilde{\mathcal{g}}_j\right) & SF\left(\widetilde{\mathfrak{w}}_{ij}\right) > SF\left(\widetilde{\mathcal{g}}_j\right) \\ 0 & SF\left(\widetilde{\mathfrak{w}}_{ij}\right) = SF\left(\widetilde{\mathcal{g}}_j\right) \\ -\mathcal{D}\left(\widetilde{\mathfrak{w}}_{ij}, \widetilde{\mathcal{g}}_j\right) & SF\left(\widetilde{\mathfrak{w}}_{ij}\right) < SF\left(\widetilde{\mathcal{g}}_j\right) \end{cases} \tag{34}$$

Finally, the distances are summed with Equation (35).

$$\mathbb{S}_j = \sum_{j=1}^{n} \Delta_{ij} \tag{35}$$

3. Results

The results obtained in this manuscript, which deals with the reduction of water use in renewable energy technologies, are presented in this section with tables and figures. Determining appropriate DMs, prioritizing criteria and ranking alternatives are shared under separate subheadings. All methods were carried out in accordance with relevant guidelines and regulations. Informed consent was obtained from all participants prior to their inclusion in the study. Participation was voluntary and participants were informed about the purpose and scope of the research.

3.1. Determining Appropriate DMs

Interview invitations are sent via e-mail to managers of companies operating in the field of renewable energy technologies and managers of R&D departments of companies producing renewable energy. 20 managers who respond positively to the e-mail are contacted as DMs for the manuscript. The professional information of the 20 DMs is summarized in Table 1.

Table 1
Professional Information

	Age	Exp in Sector	Exp as Manager	Global Exp
DM1	50	28	26	31
DM2	40	18	18	21
DM3	31	8	5	10
DM4	24	2	0	5
DM5	55	35	34	36
DM6	29	7	7	10
DM7	48	22	22	25
DM8	55	35	35	37
DM9	25	5	3	6
DM10	44	26	23	26
DM11	21	3	3	3
DM12	44	23	21	23
DM13	29	7	7	7
DM14	24	3	1	5
DM15	29	10	7	10
DM16	35	16	13	17
DM17	56	31	29	34
DM18	46	23	20	23
DM19	35	11	11	12
DM20	24	3	0	4

According to global experience in Table 1, the average experience of DMs is 17.25 and the average experience as manager of DMs is 14.25. Next, the standardized values are calculated with Equations (16) – (18). The standardized values are shared in Table 2.

Table 2
Standardized Values

	Age	Exp in Sector	Exp as Manager	Global Exp
DM1	1.116	1.105	1.052	1.224
DM2	.244	.199	.336	.334
DM3	-.541	-.706	-.828	-.645
DM4	-1.151	-1.250	-1.276	-1.091
DM5	1.552	1.739	1.768	1.669
DM6	-.715	-.797	-.649	-.645
DM7	.942	.561	.694	.690
DM8	1.552	1.739	1.858	1.758
DM9	-1.064	-.978	-1.007	-1.001
DM10	.593	.924	.783	.779
DM11	-1.413	-1.159	-1.007	-1.269
DM12	.593	.652	.604	.512
DM13	-.715	-.797	-.649	-.912
DM14	-1.151	-1.159	-1.186	-1.091
DM15	-.715	-.525	-.649	-.645
DM16	-.192	.018	-.112	-.022
DM17	1.640	1.376	1.320	1.491
DM18	.768	.652	.515	.512
DM19	-.192	-.435	-.291	-.467
DM20	-1.151	-1.159	-1.276	-1.180

Afterwards, the number of clusters is determined according to Equation (19), and equal to 3. Then, three centroids are identified randomly. The initial centroids are illustrated in Table 3.

Table 3
Initial Centroids

Cluster	Age	Exp in Sector	Exp as Manager	Global Exp
1	.768	.652	.515	.512
2	-.192	-.435	-.291	-.467
3	-1.151	-1.159	-1.276	-1.180

Next, the Euclidean distances for each DM to each centroid are calculated with Equation (20) and then, each DM is assigned by Equation (21). The results are displayed in Table 4 at the first iteration.

Table 4
Euclidean Distances (First Iteration)

	1	2	3	Cluster
DM1	1.059	2.957	4.633	1
DM2	.737	1.275	2.946	1
DM3	2.588	.718	1.031	2
DM4	3.615	1.715	.127	3
DM5	2.170	4.071	5.752	1
DM6	2.644	.752	1.000	2
DM7	.320	2.142	3.836	1
DM8	2.270	4.163	5.844	1
DM9	3.258	1.362	.380	3
DM10	.498	2.273	3.931	1
DM11	3.677	1.781	.385	3
DM12	.196	1.886	3.566	1
DM13	2.771	.855	.886	2

Table 4
Continued

	1	2	3	Cluster
DM14	3.524	1.623	.126	3
DM15	2.506	.665	1.127	2
DM16	1.414	.660	2.236	2
DM17	1.701	3.615	5.300	1
DM18	.000	1.926	3.609	1
DM19	1.926	.000	1.709	2
DM20	3.609	1.709	.000	3

At the end of first iteration, the updated centroids are obtained using Equation (22). The updated centroids at the end of first iteration are exhibited in Table 5.

Table 5
Updated Centroids at the End of First Iteration

Cluster	Age	Exp in Sector	Exp as Manager	Global Exp
1	1.000	.994	.992	.997
2	-.512	-.540	-.530	-.556
3	-1.186	-1.141	-1.150	-1.126

At second iteration, the Euclidean distances to updated centroids are calculated and shown in Table 6.

Table 6
Euclidean Distances (Second Iteration)

	1	2	3	Cluster
DM1	.285	3.321	4.552	1
DM2	1.440	1.631	2.860	1
DM3	3.358	.354	.970	2
DM4	4.377	1.324	.173	3
DM5	1.383	4.437	5.668	1
DM6	3.397	.360	.907	2
DM7	.611	2.525	3.758	1
DM8	1.479	4.529	5.758	1
DM9	4.017	.961	.278	3
DM10	.511	2.621	3.847	1
DM11	4.426	1.389	.304	3
DM12	.817	2.251	3.484	1
DM13	3.534	.498	.798	2
DM14	4.285	1.228	.064	3
DM15	3.262	.253	1.041	2
DM16	2.152	.935	2.151	2
DM17	.953	3.990	5.223	1
DM18	.796	2.300	3.534	1
DM19	2.693	.422	1.631	2
DM20	4.375	1.318	.142	3

Since the cluster information of each DM is the same in both iterations, the iteration stops. Total z is calculated with the help of Equation (23) and the clusters are compared with Kruskal Wallis. The test results are given in Table 7.

Table 7
Kruskal Wallis Result

	Age	Exp in Sector	Exp as Manager	Global Exp	N	tz	KW	p	DSCFPC*
1	48.667	26.778	25.333	28.444	9	3.983			1-2:.004
2	31.333	9.833	8.333	11.000	6	-2.138	16.5	<.001	1-3:.008
3	23.600	3.200	1.400	4.600	5	-4.604			2-3:.017

*:Dwass-Steel-Critchlow-Fligner Pairwise Comparisons

As can be seen p values in Table 7, these clusters differ statistically. When the total z values are examined, the first cluster is selected as the most successful cluster with 3.983. The average age, experience in sector, experience as manager and global experience of DMs in the first cluster are 48.667, 26.778, 25.333 and 28.444, respectively. 9 DMs in this cluster are appropriate DMs. In other words, evaluations from DM1, DM2, DM5, DM7, DM8, DM10, DM12, DM17 and DM18 are collected.

3.2. Prioritizing Criteria

At the beginning, the criteria are identified as R&D and digitalization (R&D), location selection and geographic suitability (LCLGEO), policy, incentives and regulation (PIR), education and capacity building (EDCAP), and innovative financing models (INFNN). Next, these criteria are rated by DMs using linguistic terms in Table 8.

Table 8
Linguistic Terms for Rating

	$\boldsymbol{\mu}$	$\boldsymbol{\vartheta}$
Extremely Unimportant	0.1	0.975
Not Important	0.2	0.85
Slightly Important	0.35	0.7
Moderately Important	0.55	0.5
Important	0.7	0.35
Very Important	0.85	0.2
Extremely Important	0.975	0.1

The grades of the nine DMs are summarized in Table 9.

Table 9
Grades

	R&D	LCLGEO	PIR	EDCAP	INFNN
DM1	Extremely Important	Moderately Important	Not Important	Important	Moderately Important
DM2	Extremely Important	Slightly Important	Moderately Important	Very Important	Not Important
DM5	Extremely Important	Important	Moderately Important	Very Important	Moderately Important
DM7	Moderately Important	Moderately Important	Not Important	Important	Not Important
DM8	Important	Important	Important	Important	Slightly Important
DM10	Extremely Important	Very Important	Very Important	Not Important	Not Important
DM12	Extremely Important	Moderately Important	Moderately Important	Important	Very Important
DM17	Extremely Important	Important	Not Important	Extremely Unimportant	Extremely Unimportant
DM18	Moderately Important	Very Important	Extremely Unimportant	Very Important	Moderately Important

These grades in Table 9 are transformed into Koch snowflake fuzzy numbers and the initial decision-making matrix is formed as Equation (24). The initial decision-making matrix is displayed in Table 10.

Table 10
Initial Decision-making Matrix

	R&D		LCLGEO		PIR		EDCAP		INFNN	
DM1	0.975	0.1	0.55	0.5	0.2	0.85	0.7	0.35	0.55	0.5
DM2	0.975	0.1	0.35	0.7	0.55	0.5	0.85	0.2	0.2	0.85
DM5	0.975	0.1	0.7	0.35	0.55	0.5	0.85	0.2	0.55	0.5
DM7	0.55	0.5	0.55	0.5	0.2	0.85	0.7	0.35	0.2	0.85
DM8	0.7	0.35	0.7	0.35	0.7	0.35	0.7	0.35	0.35	0.7
DM10	0.975	0.1	0.85	0.2	0.85	0.2	0.2	0.85	0.2	0.85
DM12	0.975	0.1	0.55	0.5	0.55	0.5	0.7	0.35	0.85	0.2
DM17	0.975	0.1	0.7	0.35	0.2	0.85	0.1	0.975	0.1	0.975
DM18	0.55	0.5	0.85	0.2	0.1	0.975	0.85	0.2	0.55	0.5

After obtaining the standard deviations of score functions of values in Table 10 as .270, .311, .270, .232, .184, .369, .270, .397, and .300, the multiplied values are estimated with the help of Equation (25). The multiplied values are presented in Table 11.

Table 11
Multiplied Values

	R&D		LCLGEO		PIR		EDCAP		INFNN	
DM1	0.674	0.537	0.232	0.829	0.074	0.957	0.323	0.753	0.232	0.829
DM2	0.718	0.489	0.150	0.895	0.256	0.806	0.491	0.607	0.082	0.951
DM5	0.674	0.537	0.323	0.753	0.232	0.829	0.451	0.647	0.232	0.829
DM7	0.207	0.851	0.207	0.851	0.066	0.963	0.290	0.783	0.066	0.963
DM8	0.246	0.824	0.246	0.824	0.246	0.824	0.246	0.824	0.101	0.936
DM10	0.772	0.427	0.544	0.552	0.544	0.552	0.094	0.942	0.094	0.942
DM12	0.674	0.537	0.232	0.829	0.232	0.829	0.323	0.753	0.451	0.647
DM17	0.794	0.401	0.417	0.659	0.099	0.937	0.049	0.990	0.049	0.990
DM18	0.249	0.812	0.480	0.617	0.039	0.992	0.480	0.617	0.249	0.812

Afterwards, the multiplied values are summed by Equation (26). Next, the crisped values are determined with Equation (27). The total and crisped values are shared in Table 12.

Table 12
Total and Crisped Values

	R&D		LCLGEO		PIR		EDCAP		INFNN	
$\tilde{\mathfrak{T}}$	.999	.007	.939	.073	.818	.216	.936	.083	.752	.289
$\mathcal{T}$	1.997		1.887		1.631		1.877		1.489	

Finally, the importances of criteria for prioritization are obtained using Equation (28). The importance for each criterion is visualized in Figure 2.

When the priority values of the criteria in Figure 2 are examined, the most important criteria affecting water use in renewable energy technologies are R&D and digitalization and location selection and geographic suitability.

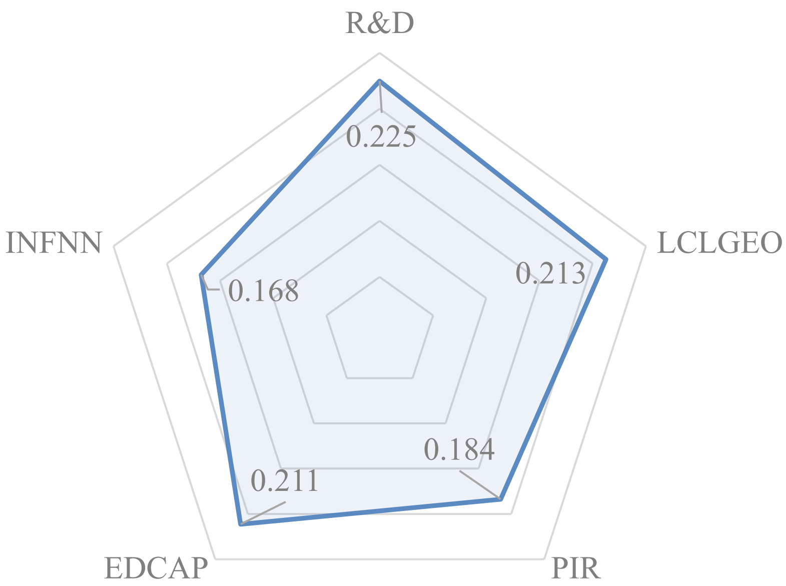

Fig. 2. Importance for Each Criterion

3.3. Ranking Investment Strategies

Firstly, the investment strategies for reducing water use in renewable energy technologies are defined as waterless panel cleaning systems (WTRLSS), dry cooling systems (DRY), robotic waterless cleaning systems (RBT), flat evaporative dam design (FLT), closed circuit cooling in geothermal energy (GEOTH), efficient irrigation systems in bioenergy agriculture (BIOA), and development of battery technology that uses water efficiently (BTRTECH).

Manual cleaning of solar energy installations is usually labor intensive and time consuming, the main reason for this is due to dust accumulation on solar panels. This situation greatly reduces efficiency. In this context, waterless panel cleaning systems consist of a two-stage mechanism that includes an ejector blower that produces a powerful air jet and a flexible brush that effectively cleans dust and sticky dirt, while cleaning intervals are strategically determined to maximize energy output [30]. In this system, the two self-cleaning coating types for anti-dust coating are super hydrophobic coating and super hydrophilicity coating. Some parameters are taken into account when evaluating the performance of the waterless panel cleaning system. These are expressed as effective cleaning, cost issues, energy usage and cleaning time, and land use [31]. In addition, ultrasonic sensors are used in these systems to adjust the position, orbit, and speed rate in real time [32].

For combined cycle power plants, the two most dominant steam condenser cooling options are wet cooling tower and dry cooling systems. In this context, dry cooling systems offer potential environmental benefits due to over 90% savings in water resources and flexibility in plant location [33]. Dry cooling systems are widely used in thermal power generation in water-scarce and coal-rich regions, and the temperature of the circulating cooling water increases when the system is operating because it absorbs the latent heat of the steam turbine exhaust in the condenser [34]. In addition, for the comprehensive design and selection of dry cooling systems, thermal performance under design or off-design conditions, power cycle, economic performance of the dry cooling system, and environmental conditions where the thermal power plant is located are important issues to be considered [35].

The fact that distributed photovoltaic power stations are installed at high altitudes makes cleaning difficult. For this reason, a new waterless cleaning robot is proposed for dust removal from photovoltaic panels, especially in areas with water scarcity. While the material, structure and sealing device of the robot are optimized according to the carrying capacity and operating efficiency of the photovoltaic system, a roller brush and negative pressure method are developed for dust collection [36]. In other words, an unmanned, low-cost robotic device that works without rails or guides for waterless dust and sand cleaning from the surface of photovoltaic panels moves autonomously as a half-track. It also gently wipes the dust by means of several independent helical brushes that rotate alternately according to a defined combination of cleaning and movement strategy [32]. In short, robotic waterless cleaning systems are being developed to eliminate the disadvantages of manual cleaning, such as personnel accidents and inadequate maintenance [37].

Evaporation is primarily a primary component of the hydrological cycle, water resources management and forward planning. For the dam system, successful management is based on accurate estimation of reservoir evaporation magnitude [38]. In fact, evaporation is higher near the exposed soil or dam, which transfers more heat to the water [39]. The crest dam design offers a solution to water scarcity in the study area and other semiarid regions, facilitating the channeling and storage of winter water, thus ensuring water availability during the dry season. In addition, it is more economical and feasible than large hydraulic projects, as it collects excess rainwater and utilizes local materials in the construction of the dam body [40].

Closed-circuit cooling is prominent in geothermal energy. The purpose of the geothermal system is to capture the thermal energy of the geothermal fluid and use it to generate electricity. The system is based on a binary cycle technology with a geothermal fluid extraction and reinjection circuit and another closed circuit of an organic working fluid and is also characterized by its high volatility and low boiling point [41]. In closed-circuit cooling systems, water does not evaporate or disappear as in open systems, but can be reused, demonstrating the high efficiency and reliability of the current integrated closed cooling system [42]. In other words, the system responds to the lower energy load by reducing the water flow, which facilitates the thermal recovery of the soil [43].

Smart irrigation systems are compatible with the renewable energy potential and the need for sustainable agricultural practices and offer a promising solution. The best examples of this are evaluating the effectiveness of soil and atmospheric moisture sensors, analyzing water distribution efficiency, and assessing the feasibility of deep groundwater extraction [44]. In addition, it is possible to say that efficient irrigation systems can provide clean, climate-smart, and innovative energy technologies, which can provide socioeconomic and environmental benefits [45]. In other words, as more efficient irrigation systems are used, the volume of irrigation water can be reduced, thus reducing agricultural water demand [46].

The development of battery technologies that use water efficiently is important in the storage phase of energy obtained from renewable energy sources. Indeed, sudden and widespread changes in energy production or use are of critical importance to secure our future [47]. While a breakthrough is being made in the field of energy storage systems, especially in the development of battery technologies, aqueous zinc-ion batteries are becoming the center of attention due to the excess zinc resources found in the earth's crust and their affordable price compared to lithium [48]. In short, the development of an integration model or framework for the applications of smart water management systems also supports the development of battery technologies that use water efficiently [49]. Then, these investment strategies are evaluated by DMs using linguistic terms in Table 13.

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Table 13
Linguistic Terms for Ranking

	μ	ϑ
Inadequate	.1	.975
Very Poor	.2	.9
Poor	.3	.8
Medium Poor	.4	.65
Medium	.55	.5
Medium Good	.65	.4
Good	.8	.3
Very Good	.9	.2
Exceptional	.975	.1

The evaluations of the nine DMs are shown in Table 14, respectively.

Table 14
Evaluations

	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Exceptional	Very Poor	Medium Poor	Very Good	Medium Poor
DRY	Good	Medium Poor	Medium Good	Medium Good	Medium Good
RBT	Medium	Very Poor	Medium Poor	Very Poor	Very Good
FLT	Good	Good	Inadequate	Medium	Medium Poor
GEOTH	Medium Poor	Good	Good	Inadequate	Medium Good
BIOA	Inadequate	Good	Medium Good	Good	Inadequate
BTRTECH	Very Good	Very Good	Good	Exceptional	Exceptional
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Very Poor	Medium Poor	Good	Medium	Medium Good
DRY	Good	Medium Good	Good	Medium	Medium Poor
RBT	Medium Poor	Inadequate	Good	Medium Poor	Medium
FLT	Poor	Medium Good	Exceptional	Exceptional	Poor
GEOTH	Inadequate	Medium	Poor	Poor	Very Good
BIOA	Inadequate	Medium Poor	Very Good	Exceptional	Medium Good
BTRTECH	Good	Exceptional	Exceptional	Good	Exceptional
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Medium	Very Good	Good	Very Poor	Medium Poor
DRY	Good	Medium	Medium	Medium Good	Good
RBT	Medium	Medium Poor	Medium	Medium	Very Good
FLT	Very Good	Medium	Exceptional	Medium Poor	Very Good
GEOTH	Very Poor	Inadequate	Inadequate	Medium Poor	Medium Poor
BIOA	Exceptional	Good	Very Good	Exceptional	Inadequate
BTRTECH	Exceptional	Exceptional	Very Good	Good	Exceptional
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Very Poor	Very Good	Poor	Very Good	Inadequate
DRY	Good	Medium	Medium Good	Medium Poor	Very Good
RBT	Exceptional	Medium Good	Medium	Good	Very Good
FLT	Inadequate	Medium	Medium	Good	Medium
GEOTH	Very Poor	Medium Good	Exceptional	Good	Exceptional
BIOA	Poor	Good	Exceptional	Exceptional	Inadequate
BTRTECH	Very Good	Medium Good	Very Good	Very Good	Medium Good
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Medium	Medium Poor	Medium	Poor	Exceptional
DRY	Medium	Medium Good	Medium Good	Very Good	Medium Poor
RBT	Very Poor	Good	Medium	Medium	Medium Good
FLT	Exceptional	Very Poor	Very Poor	Poor	Very Poor
GEOTH	Exceptional	Medium Poor	Medium Good	Good	Good

Table 14
Continued

	R&D	LCLGEO	PIR	EDCAP	INFNN
BIOA	Very Poor	Very Poor	Inadequate	Very Poor	Inadequate
BTRTECH	Medium Good	Medium	Medium	Medium	Medium
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Good	Medium Poor	Medium	Inadequate	Medium Good
DRY	Medium Poor	Medium Good	Good	Very Good	Medium Poor
RBT	Inadequate	Inadequate	Inadequate	Very Good	Very Poor
FLT	Medium	Very Poor	Medium Good	Medium Good	Poor
GEOTH	Medium Good	Poor	Exceptional	Very Good	Inadequate
BIOA	Medium Poor	Medium Good	Poor	Very Good	Very Good
BTRTECH	Medium	Very Good	Medium	Very Good	Good
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Medium Poor	Medium Poor	Good	Inadequate	Inadequate
DRY	Medium	Medium Poor	Good	Good	Medium Good
RBT	Medium	Good	Very Poor	Good	Medium Poor
FLT	Poor	Medium	Medium Good	Inadequate	Inadequate
GEOTH	Poor	Very Poor	Good	Medium Poor	Medium
BIOA	Medium	Exceptional	Medium Poor	Medium	Very Poor
BTRTECH	Medium Good	Medium	Very Good	Very Good	Exceptional
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Very Good	Good	Good	Medium	Very Good
DRY	Very Good	Medium	Very Good	Medium Good	Medium Good
RBT	Exceptional	Very Good	Good	Very Poor	Exceptional
FLT	Inadequate	Good	Exceptional	Good	Very Good
GEOTH	Exceptional	Very Good	Very Poor	Very Poor	Medium Good
BIOA	Exceptional	Medium	Medium Good	Medium Poor	Medium Good
BTRTECH	Good	Medium Good	Medium	Medium	Good
	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	Good	Very Poor	Exceptional	Medium Good	Exceptional
DRY	Medium	Medium	Medium Good	Medium	Good
RBT	Good	Medium	Inadequate	Medium	Medium
FLT	Very Good	Medium	Good	Poor	Medium Poor
GEOTH	Good	Exceptional	Very Poor	Inadequate	Very Good
BIOA	Good	Very Good	Medium	Exceptional	Medium
BTRTECH	Exceptional	Medium	Medium Good	Medium Good	Very Good

Afterwards, these evaluations in Table 14 are transformed into Koch snowflake fuzzy numbers regarding to Table 13. Next, the average of these numbers is computed using Equation (11) and using the average values as elements, the decision matrix is constructed as Equation (29). The decision matrix is expressed in Table 15.

Table 15
Decision Matrix

	R&D		LCLGEO		PIR		EDCAP		INFNN	
WTRLSS	1.000	.396	1.000	.493	1.000	.361	1.000	.519	1.000	.370
DRY	1.000	.371	1.000	.492	1.000	.345	1.000	.368	1.000	.408
RBT	1.000	.391	1.000	.501	1.000	.569	1.000	.473	1.000	.330
FLT	1.000	.415	1.000	.496	1.000	.302	1.000	.448	1.000	.552
GEOTH	1.000	.429	1.000	.434	1.000	.394	1.000	.558	1.000	.340
BIOA	1.000	.444	1.000	.342	1.000	.379	1.000	.229	1.000	.617
BTRTECH	1.000	.242	1.000	.271	1.000	.284	1.000	.268	1.000	.192

After that, the average values are normalized with Equation (30). Because all criteria in manuscript are beneficial. In other words, the decision matrix and the normalized matrix are the same. Afterwards, the values are multiplied by the coefficients in Figure 2 using Equation (32) and the weighted decision matrix is displayed in Table 16.

Table 16
Weighted Decision Matrix

	R&D		LCLGEO		PIR		EDCAP		INFNN	
WTRLSS	0.938	0.812	0.912	0.861	0.910	0.830	0.901	0.871	0.880	0.846
DRY	0.945	0.800	0.913	0.860	0.913	0.822	0.934	0.810	0.879	0.861
RBT	0.936	0.810	0.906	0.864	0.860	0.902	0.915	0.854	0.896	0.830
FLT	0.932	0.821	0.912	0.862	0.917	0.803	0.917	0.844	0.843	0.905
GEOTH	0.929	0.827	0.920	0.838	0.897	0.843	0.895	0.884	0.892	0.835
BIOA	0.925	0.833	0.939	0.796	0.902	0.837	0.956	0.733	0.814	0.922
BTRTECH	0.963	0.727	0.950	0.758	0.926	0.794	0.951	0.757	0.930	0.758

Next, the geometric average for each criterion in Table 16 is calculated by Equation (33). The geometric average values are shown in Table 17.

Table 17
Geometric Average Values

	R&D		LCLGEO		PIR		EDCAP		INFNN	
$\tilde{g}$	0.938	0.807	0.921	0.838	0.903	0.837	0.924	0.829	0.876	0.860

After that, the distance between alternatives and geometric averages is computed with the help of Equation (34). The distance results are given in Table 18.

Table 18
Values

	R&D	LCLGEO	PIR	EDCAP	INFNN
WTRLSS	-0.01233	-0.05498	0.00000	-0.09960	0.00000
DRY	0.00029	-0.05368	0.00000	0.00000	0.01108
RBT	-0.00738	-0.06205	-0.15796	-0.05843	0.00000
FLT	-0.03342	-0.05740	0.00000	-0.03510	-0.11047
GEOTH	-0.04824	-0.00476	-0.01556	-0.13188	0.00000
BIOA	-0.06334	0.00000	-0.00380	0.00000	-0.15280
BTRTECH	0.00000	0.00000	0.00000	0.00000	0.00000

Finally, the values in Table 18 are summed using Equation (25). The $\mathbb{S}$ values and ranks of investment strategies for reducing water use in renewable energy technologies are summarized in Figure 3.

As can be seen rank values in Figure 3, the optimal investment strategy for reducing water use in renewable energy technologies is development of battery technology that uses water efficiently. The second investment strategy is dry cooling systems.

3.4. Comparison and Sensitivity Analyses

Comparison and sensitivity analyses are applied to ensure consistency and validity of the results. While RATGOS is preferred as a second method for comparative analysis, analyses are repeated with two methods with minimal changes in criterion weights for sensitivity analysis. The results of the two types of analyses are shared in Table 19.

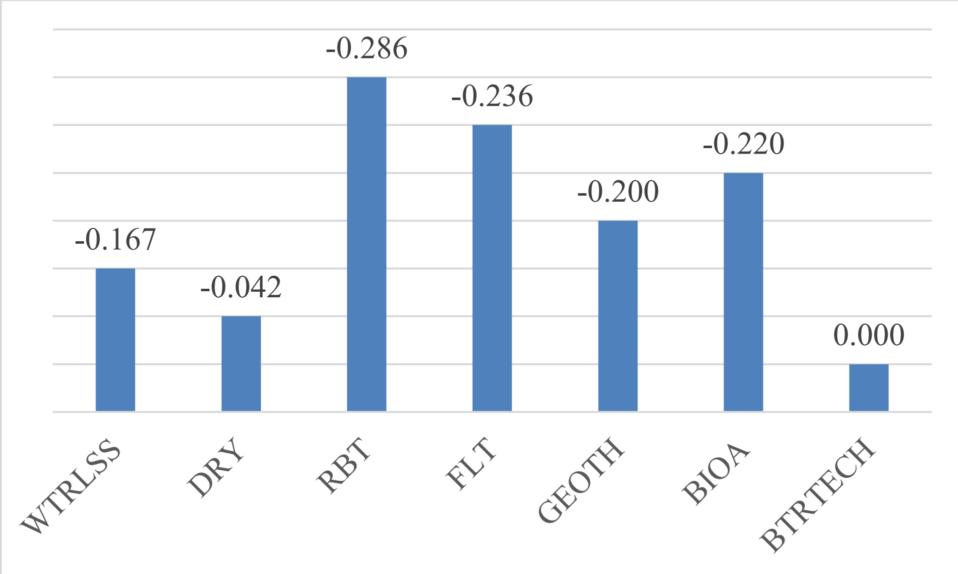

Fig. 3. Ranking of Investment Strategies

Table 19
Comparison and Sensitivity Analyses

	MABAC				RATGOS			
	SA1	SA2	SA3	SA4	SA1	SA2	SA3	SA4
WTRLSS	3	3	3	3	4	4	4	4
DRY	2	2	2	2	2	2	2	2
RBT	7	7	7	7	7	7	7	7
FLT	6	6	6	6	5	5	5	5
GEOTH	4	4	4	4	6	6	6	6
BIOA	5	5	5	5	3	3	3	3
BTRTECH	1	1	1	1	1	1	1	1

The rankings of two methods are similar. According to both methods, the two most optimal investment strategies for reducing water use in renewable energy technologies are the same, indicating that the results are consistent and valid.

4. Conclusion

There are many criteria for reducing the use of water in renewable energy technologies. The most important of these criteria is R&D and digitalization. Research and development studies contribute to the development of technology and support the fight against climate change and sustainable development [50]. In this context, Nkinyam *et al.,* [30] proposed waterless solar panel cleaning technology in their study. With this technology, the use of water in solar energy production will be reduced. In another study, Kılkış *et al.,* [51] stated that renewable energy technologies will minimize environmental damage along with carbon-free energy production. In the study, it is emphasized that energy systems should be developed to ensure energy-water optimization. In another similar study, Kuzmin *et al.,* [52] reported that digitalization in the energy sector will positively affect renewable energy production. In the study, the importance of digitalization in terms of sustainability was emphasized. It is emphasized that advanced human capital is important in digitalization and adoption of new technologies. Finally, Choi *et al.,* [53] indicated that ensuring water recycling will reduce water use. It is emphasized that studies for recycling water will reduce water use in energy production.

Site selection and geographical suitability are among the important criteria for water conservation in renewable energy technologies. The amount of water used in energy production is largely related to the geographical characteristics, climatic conditions, proximity to natural resources and infrastructure facilities [54]. Site selection and geographical suitability reduce the pressure on existing water resources in renewable energy production. As a matter of fact, Kotb *et al.,* [55] emphasized in their study that different energy systems will be suitable in regions with different geographical characteristics. In this way, water will be used more effectively. In another similar study; Okedu *et al.,* [56] stated that the potential of renewable energy sources should be determined, and the facility should be in accordance with this potential. Şahin *et al.,* [57] expressed that site selection in renewable energy facilities will reduce energy production costs. In the study, it was underlined that determining the appropriate location and ensuring geographical suitability will increase efficiency.

One of the most effective criteria for saving water in renewable energy sources is water-efficient batteries. Batteries designed in this way both increase energy storage capacity and contribute to water savings. Water-efficient batteries, a technology that strengthens sustainability in the water-energy relationship, reduce dependence on traditional systems [58]. These systems provide energy supply security by storing more energy due to the use of advanced technology. Allouhi [59] proposed water-efficient battery technologies to provide clean energy and support sustainable development. To use water efficiently, the article suggests using water from the river on which the hydroelectric power plant is located. Another effective alternative to save water is dry cooling systems for solar panels. Dry cooling systems are cooling technologies that provide heat exchange with air flow instead of water [60]. While wet systems consume about 2-3 tons of water for cooling, this amount is almost zero in dry cooling systems.

Energy policies in the European Union are being reshaped by environmental, economic and political developments. The importance of renewable resources has increased, especially when the political tensions around it threaten the security of energy supply [61]. Practices and legal regulations for the use of renewable energy implemented in the European Union increase the production and use of renewable energy. Accordingly, interest in renewable energy has increased in recent years. Similarly, political crises such as wars in countries from which Europe imports energy have also brought the security of energy supply to the agenda [62]. For this reason, energy interruptions reaching crisis proportions have occurred in various countries of Europe. In this respect, the European Union is emphasizing the goal of diversifying energy supply sources and rapidly expanding renewable energy [63].

When the relevant literature is examined, it is determined that most of the Europe's energy is provided from renewable energy sources. In particular, the energy obtained from solar, and wind has come to the forefront in ensuring Europe's energy transformation [64]. The European Union is called the pioneer of renewable energy in the world due to its renewable energy investments [65]. Maintaining this leadership is important for energy security and economic competitiveness. Recent developments have mobilized the European Union on energy and emphasized that external dependence on energy is a strategic weakness. Renewable energy investments are considered as the most effective way to overcome this weakness. For this reason, renewable energy investments benefit the European Union countries both in addressing concerns about climate change and in providing safe and uninterrupted energy.

This study identifies strategies to reduce excessive water consumption in renewable energy technologies according to their significance levels. A novel model is generated by integrating cluster-based expert selection, SIWEC and MABAC methods. Furthermore, Koch Snowflake fuzzy sets are developed and integrated into the decision-making model to overcome uncertainties more effectively. It is identified that the most effective investment strategy in reducing water consumption is the development of battery technologies that use water efficiently. This study contributes to the systematic prioritization approach missing in the literature by analyzing the importance levels of strategies to reduce excessive water consumption in renewable energy technologies under uncertainty. The Koch Snowflake structure is based on fractal geometry. With the help of considering these new sets, uncertainties in complex and multi-layered systems can be represented more successfully. Integrating the clustering-based expert selection technique into the decision-making model provides methodological advantages.

The decision-making model used in the study is based on expert opinions. However, since the number of experts is limited, the results obtained may differ with a wider expert audience. This may limit the generalizability of the model. To eliminate this limitation, future studies can include the opinions of more experts from different countries and sectors. Renewable energy and water efficiency technologies are constantly evolving. Therefore, the priority rankings of the strategies determined in the study may change over time. This situation can be considered as another limitation of the study. To eliminate this problem, artificial intelligence-supported dynamic decision-making models that are more sensitive to technological changes can be developed in the next studies. The applicability of the strategies may vary geographically, and country based. This study constitutes a limitation because it presents a general approach. As a future research direction, the practical validity of the model can be tested with case studies that evaluate the effects of the strategies in local contexts.

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Conflicts of Interest
The authors declare no conflicts of interest.

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